



DEEP Rob

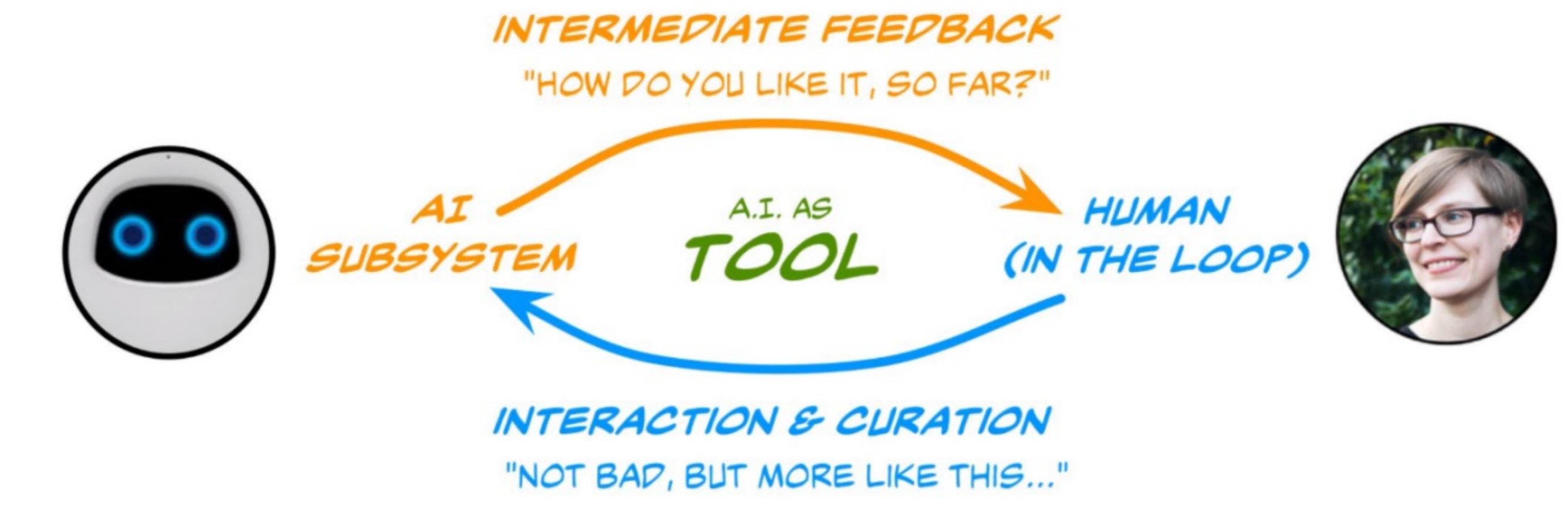
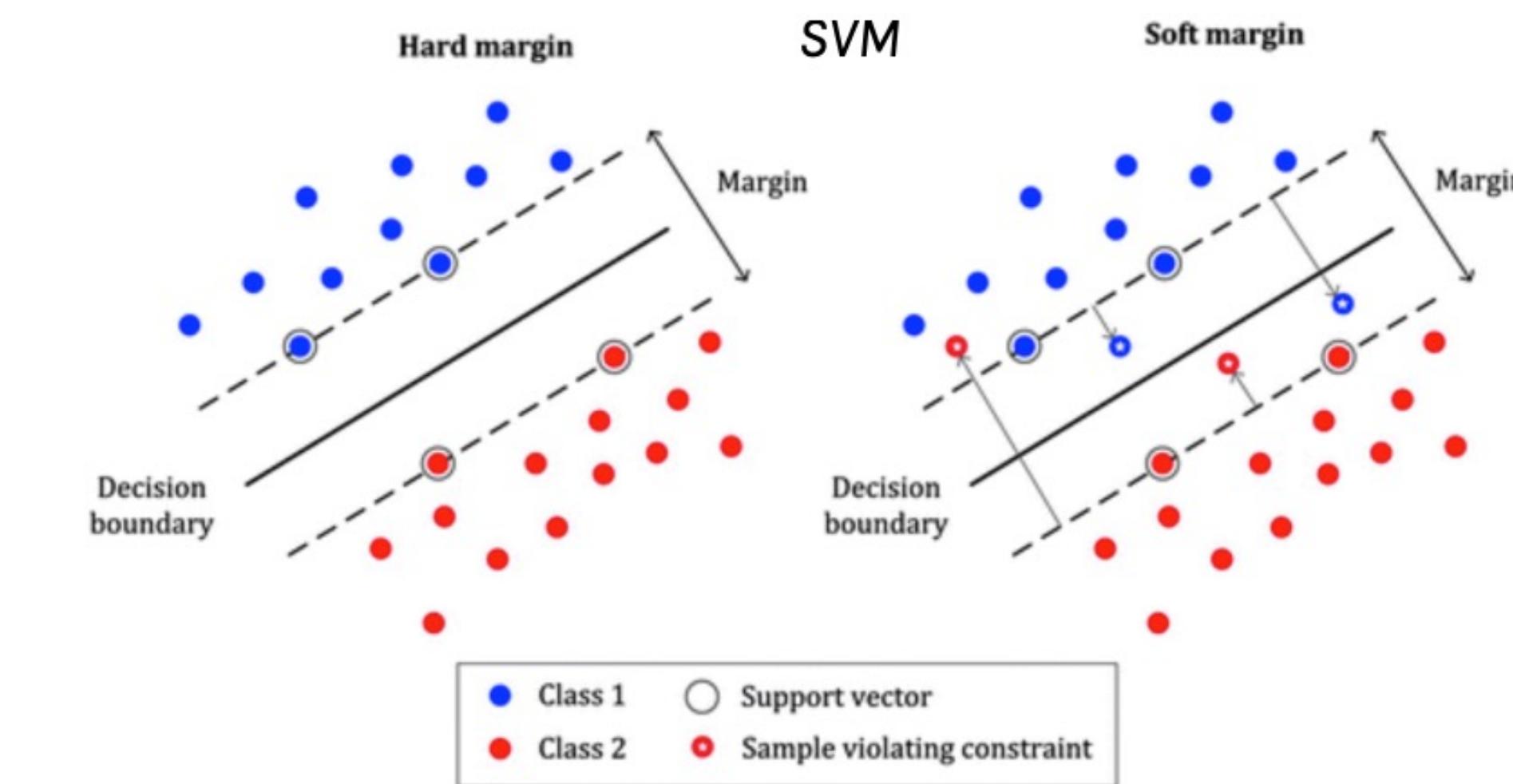
Lecture 18
Interpretability and Uncertainty
University of Michigan | Department of Robotics





Why Interpretability

- Trust
- Safety
- Contestability/Reproducibility



Stanford, Humans in the Loop General Blueprint
*Some figures adapted from Harvard AC295 Lecture 11



Transparent Model

- Visualize feature maps:
- Saliency Map
- Class Activation Maximization (CAM)

Answers this question: What made the network give a certain class as output?

e.g., Why is it classifying this image as “dog”?



Saliency Map

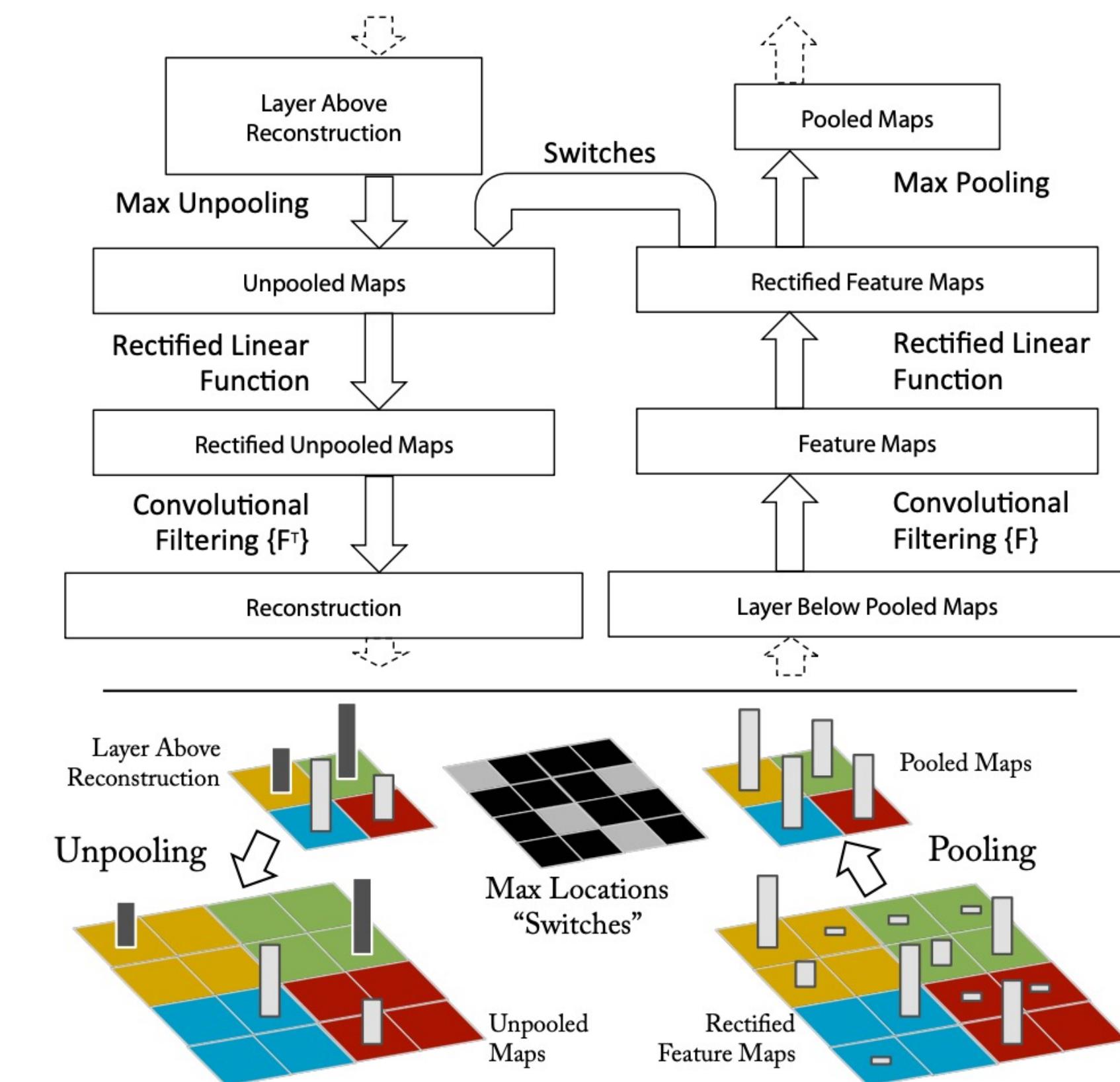
- (we didn't talk about this in class but good to know)

“a way to measure the spatial support of a particular class in each image”

Common method:

Deconvolution (Zeiler and Fergus, 2013)

<https://arxiv.org/abs/1311.2901>





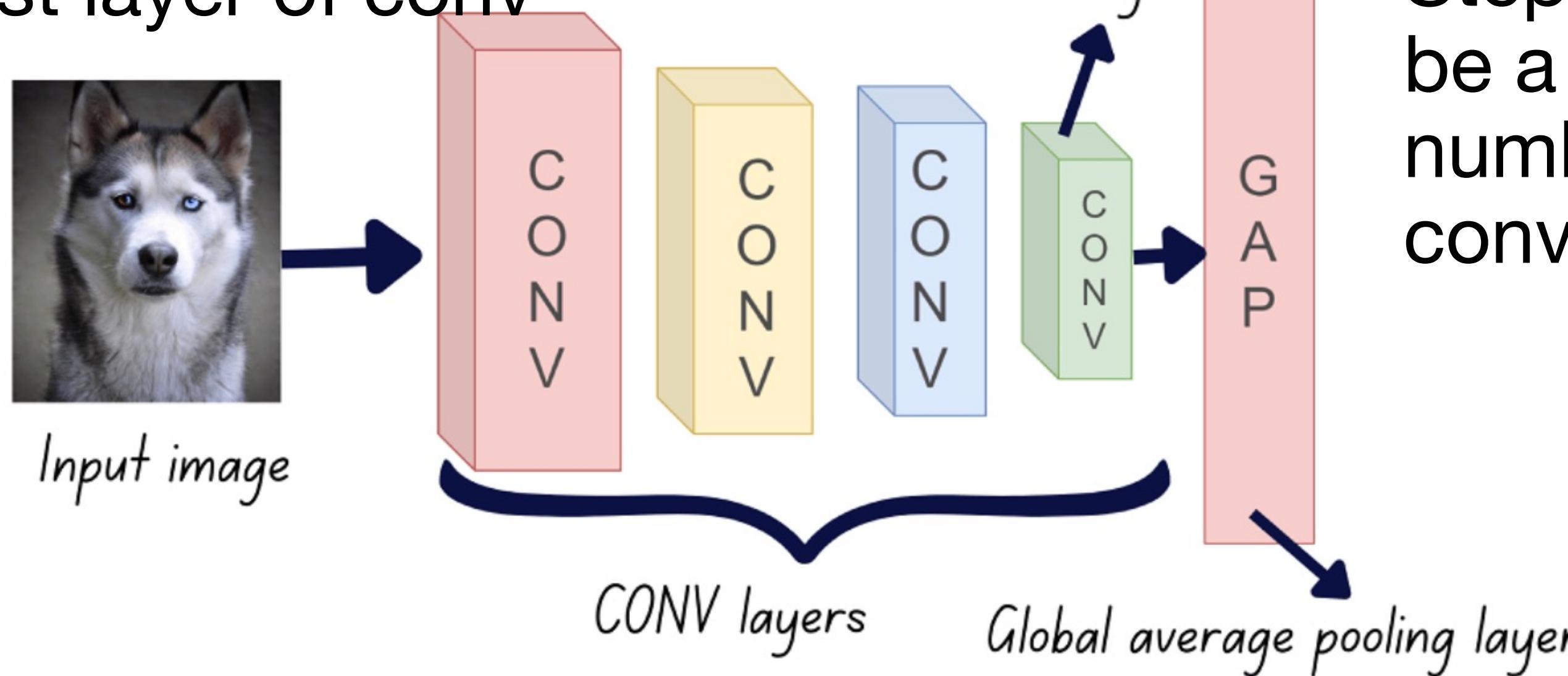
CAM

Step 2: GAP (Global average pooling)

Take the average of feature map -> scalar

- Class Activation Map

Step 1: last layer of conv



Feature map #1

a1	a2	a3
a4	a5	a6
a7	a8	a9

$$\rightarrow k_1 = \frac{a_1 + a_2 + \dots + a_9}{9}$$

Step 3: The output of GAP will be a n-length vector, for n is the number of feature maps (from conv)

Vector of scalars,
 $k_i = \text{avg. of feature map } \#i$

$$\begin{matrix} \text{G} \\ \text{A} \\ \text{P} \end{matrix} \rightarrow \begin{bmatrix} k_1 \\ k_2 \\ k_3 \\ \vdots \\ k_n \end{bmatrix}$$

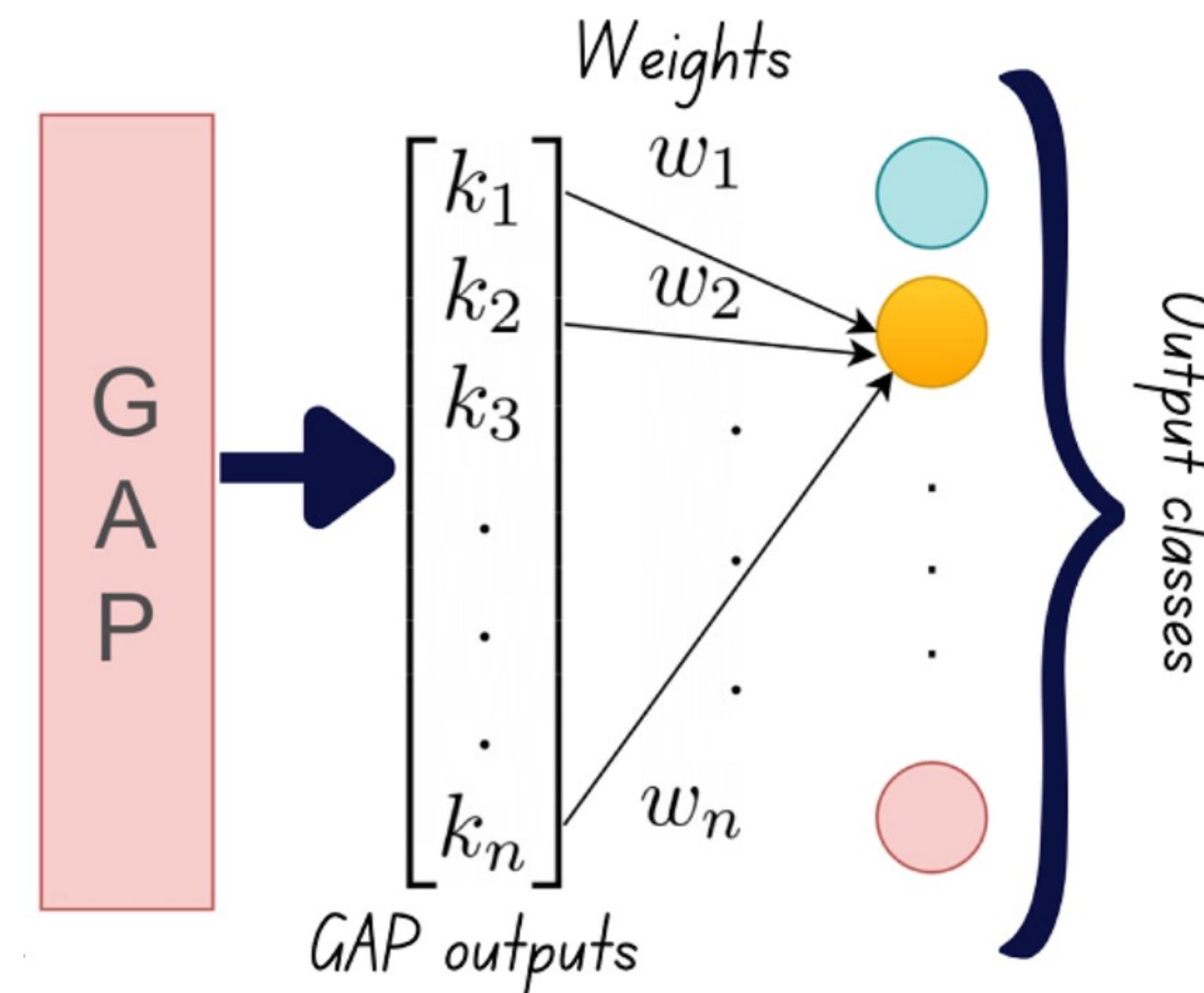


CAM

- Class Activation Map

*This captures the relationship between feature maps learned from Conv to class labels!

Step 4: train a linear model to learn the weights between GAP vector outputs and class labels



We will train this C times for C classes

$$y^c = \sum_k w_k^c \frac{1}{Z} \sum_i \sum_j A_{ij}^k$$

c – class

k - k^{th} feature map, $k=1, \dots, n$

Z – total number of pixels

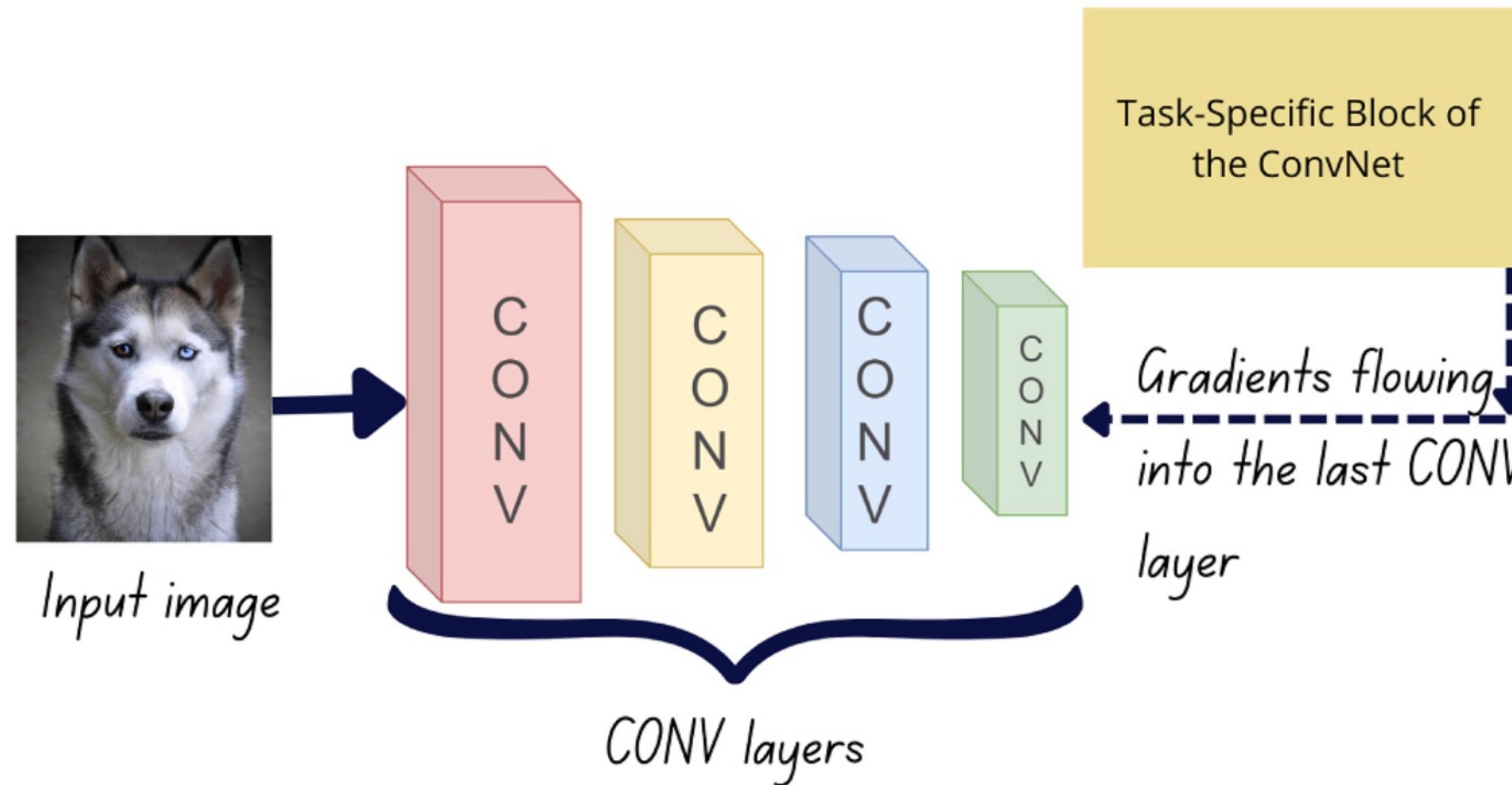
A_{ij}^k - the pixel value at (i,j) for the k^{th} feature map



Grad-CAM

- Gradient-Weighted Class Activation Maps

*Use backprop to flow gradients from output class score y^c to the feature maps



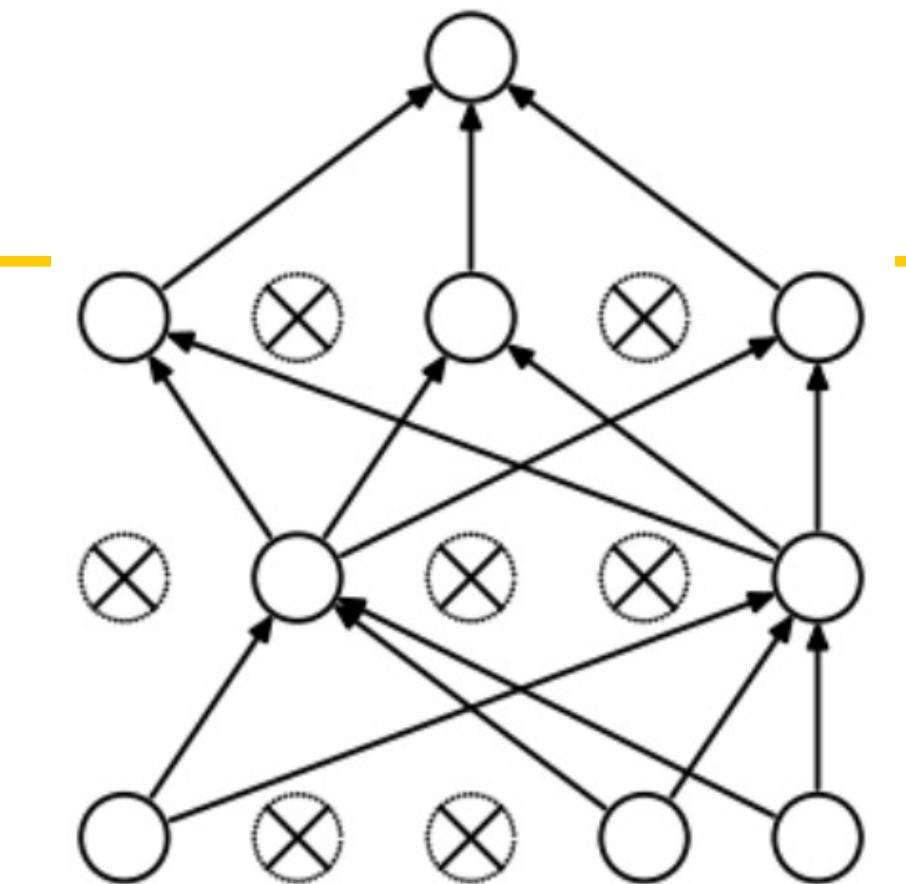
$$w_k^c = \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k}$$

$$L_{grad-cam}^c = \text{ReLU} \left(\sum_k w_k^c A^k \right)$$



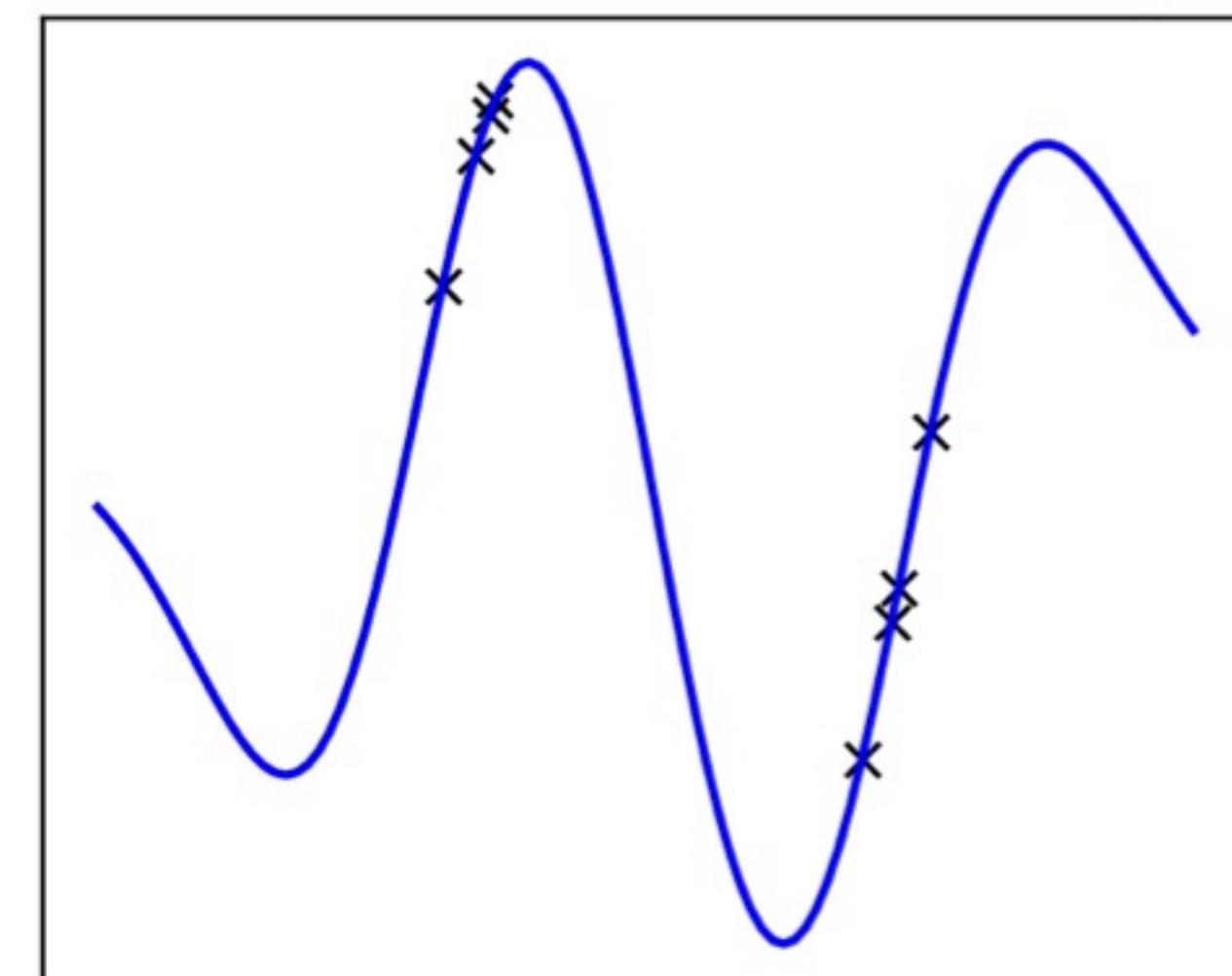
Model with Uncertainty

- Uncertainty in data, label/annotations, model, etc...

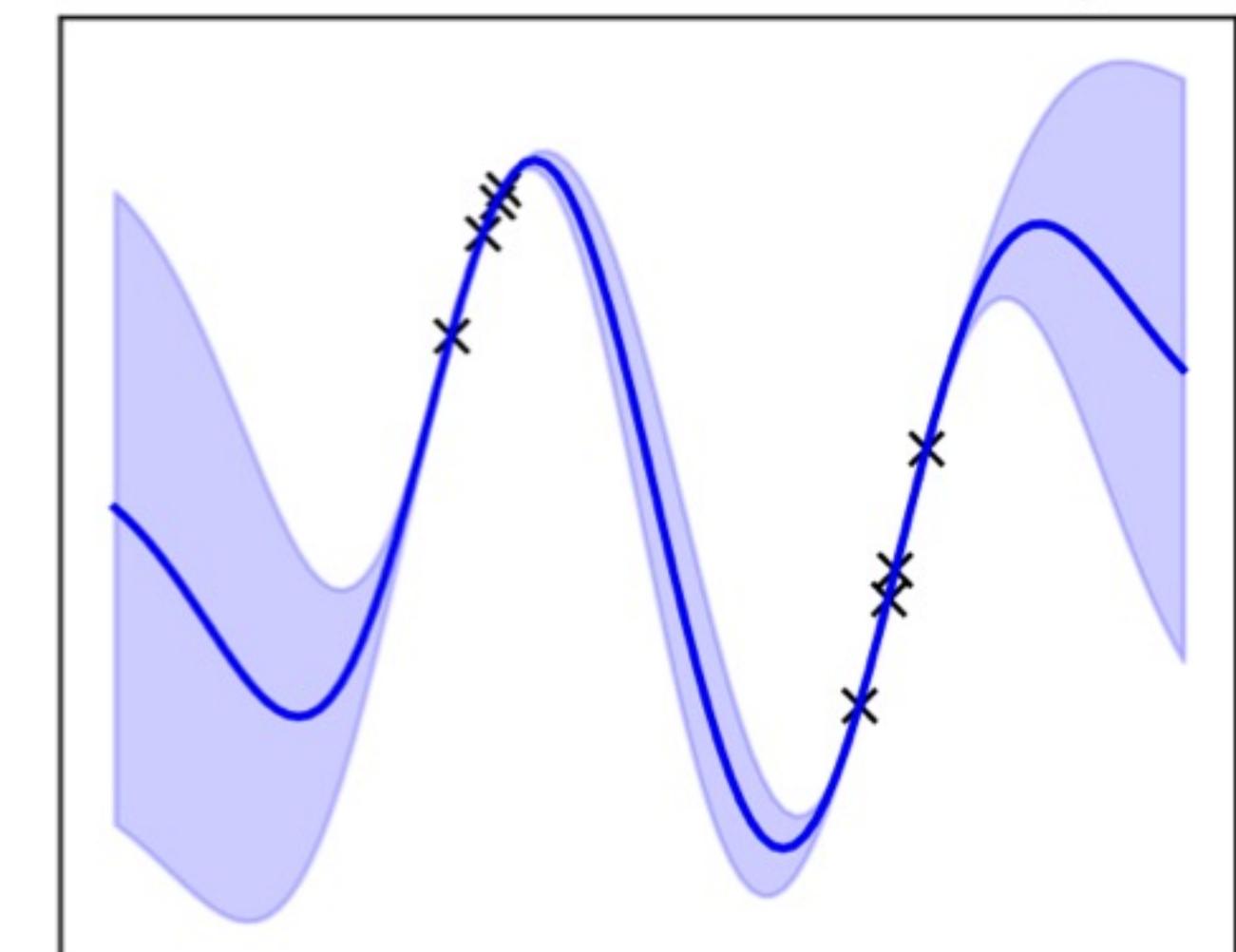


- Examples (not limited to):
 - 1. Dropout
 - 2. Bayesian Neural Networks

Prediction without uncertainty



Prediction with uncertainty

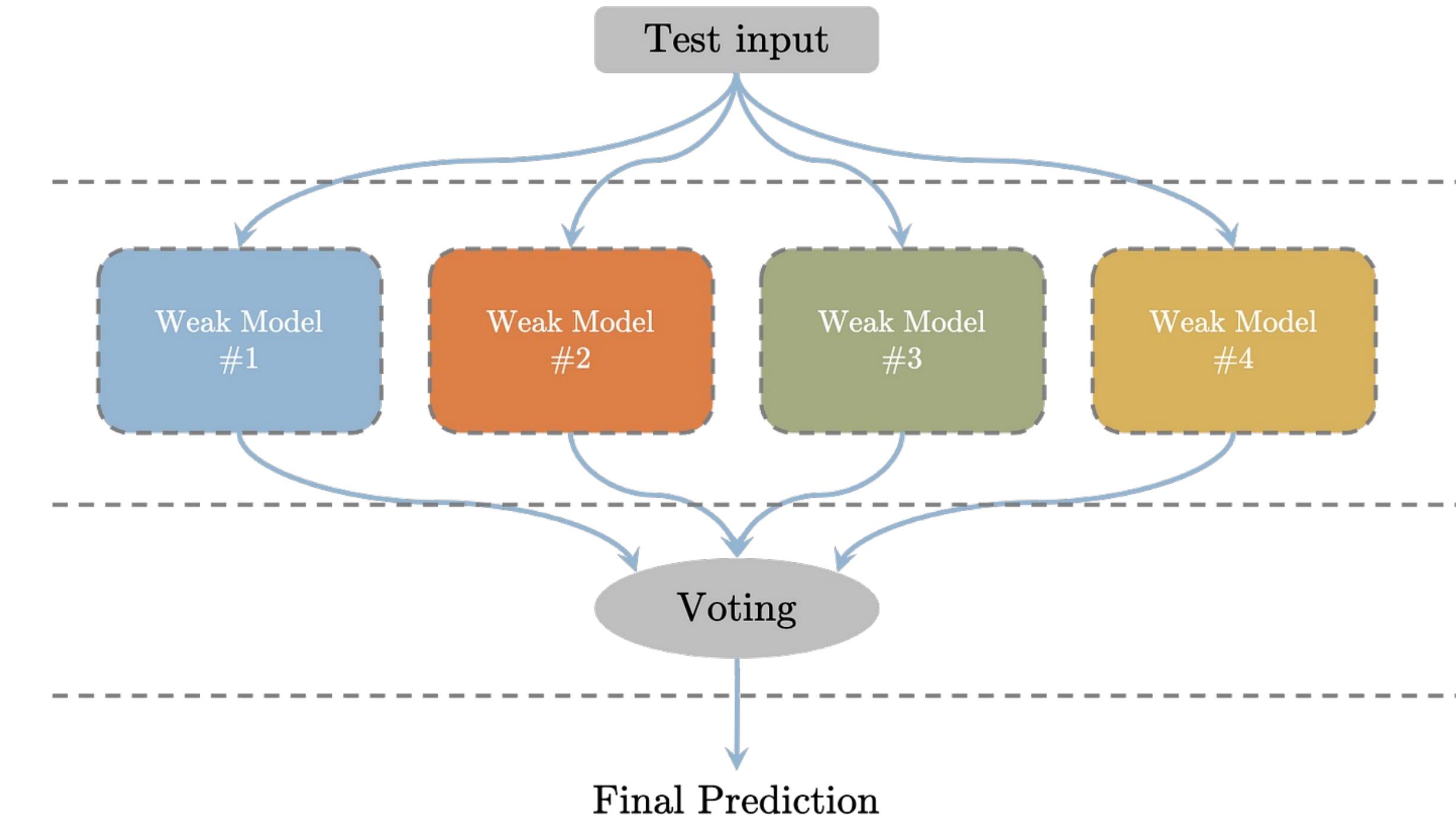




Model with Uncertainty

- Uncertainty in data, label/annotations, model, etc...

- Examples:
- Dropout
- Bayesian Neural Networks
- **3. Ensemble Methods**

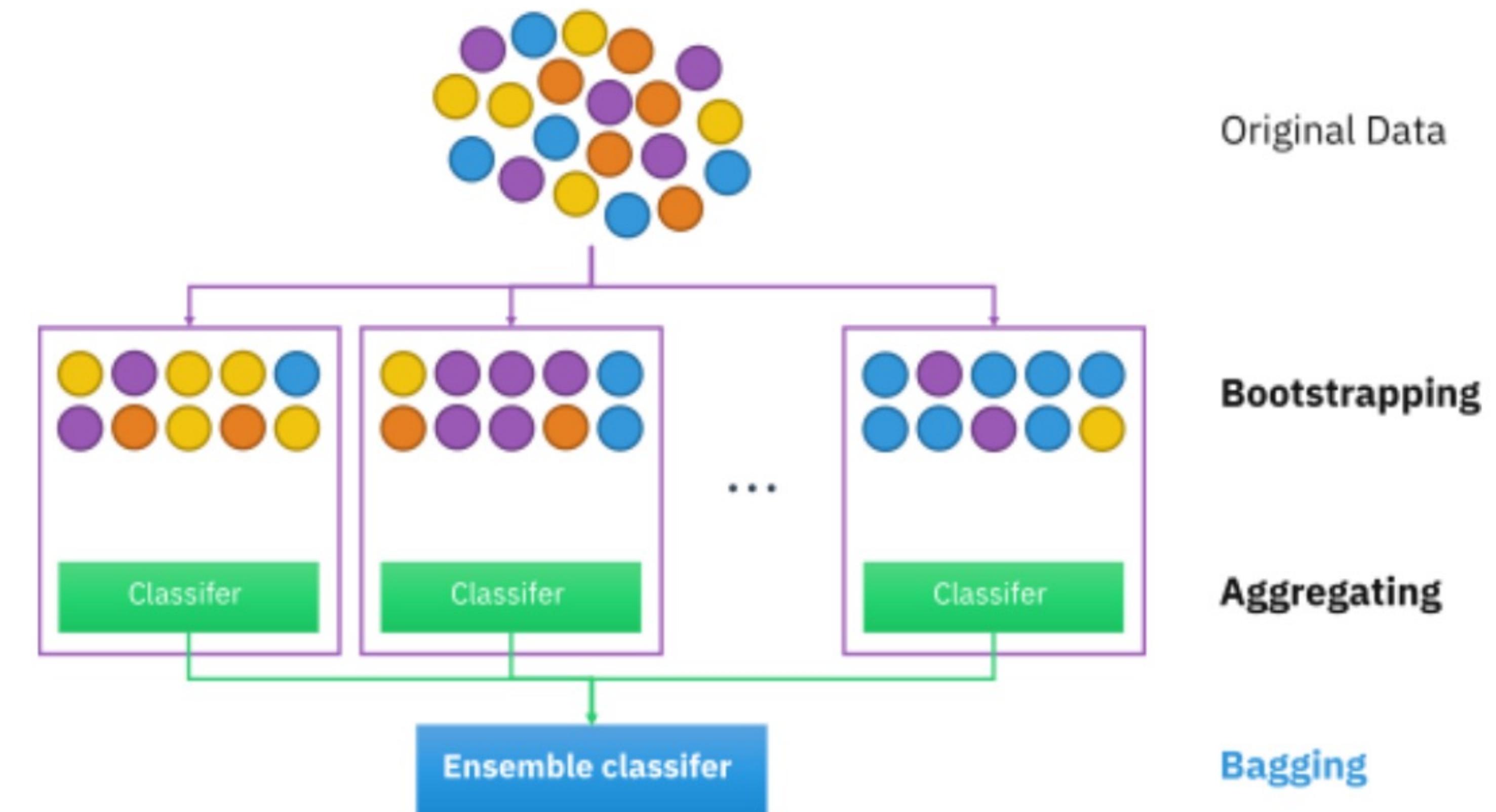




Model with Uncertainty

- Uncertainty in data, label/annotations, model, etc...

- Examples:
- Dropout
- Bayesian Neural Networks
- Ensemble Methods
- **4. Bootstrap Aggregating (Bagging)**
- Multiple Instance Learning



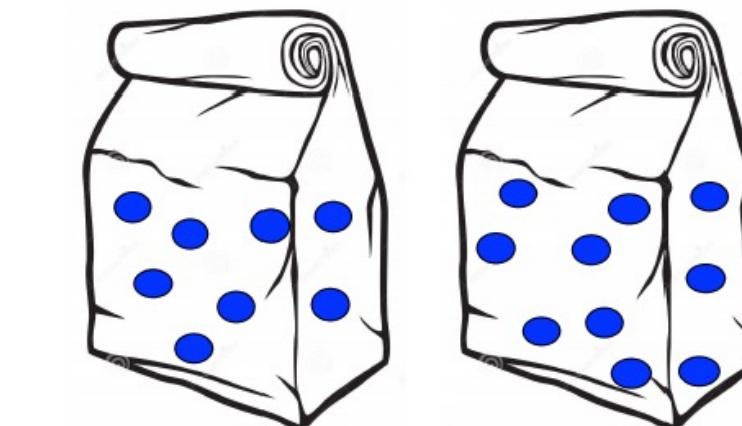


Model with Uncertainty

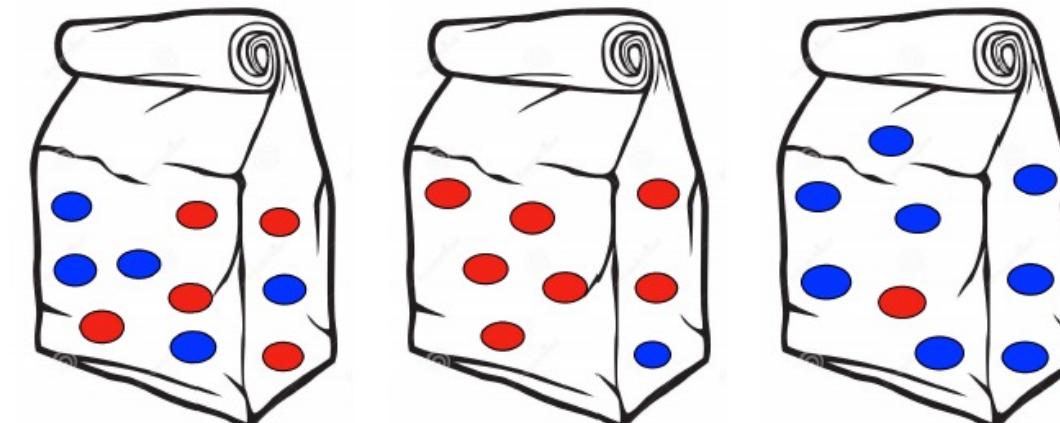
- Uncertainty in data, label/annotations, model, etc...

- Examples:

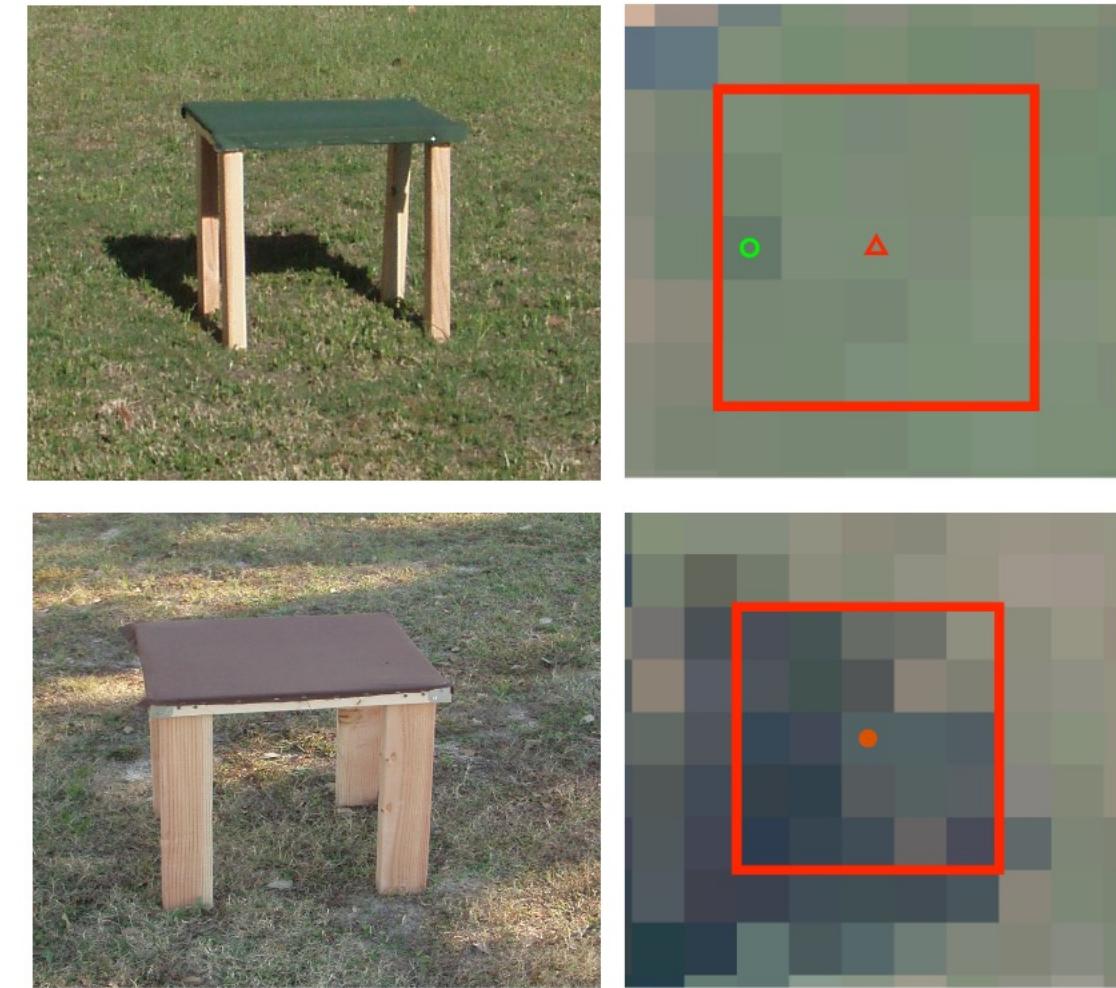
- Dropout
- Bayesian Neural Networks
- Ensemble Methods
- Bootstrap Aggregating (Bagging)
- **5. Multiple Instance Learning**



Negative Bags



Positive Bags



“label uncertainty”
Design loss function based on “bag-level” labels



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